A Study Protocol for Randomized Trials on Visual ERP for multiclass discrimination in CAAD applications

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STUDY PROTOCOL

A Study Protocol for Randomized Trials on Visual ERP for multiclass discrimination in CAAD applications

Pierre Cutellic* and Nauman Khalid Qureshi

Abstract

Background: A great part of brain-computer interfaces (BCI's) research has so far, been focusing on interactions using exogenous responses under selective attention with synchronous and reactive methods for clear relation with controlled stimuli and the widespread applicability of the methods. Over the two past decades, event-related potentials (ERP's) have become more and more investigated for a broader community of researchers due to the relatively little amount of training necessary for a system to perform and their detection across diverse modalities of acquisition to correlate with the sensory discrimination of dedicated stimuli. The proposed study aims to observe the detection of ERP's components and correlated neural phenomena under the visual presentation of complex stimuli and devise processing methods that would generalize their classification for applications in computer-aided architectural design (CAAD), where visual complexity becomes an intrinsic feature of the tasks.

Methods: Its objective is exploratory and twofold: evaluating data processing and stimulus presentation methods, as well as the evolution of similar responses in repeated measures intra- and inter-subjects in non-clinical states. The study is divided into 4 phases of offline-online experiments across its timeline. Offline experiments are used to study and validate base methods, and online experiments are used to validate their modifications for application usage. Each of these experiments are framed by cross-sectional and longitudinal sub-studies. The chosen neural phenomena and study, as well as the presentation paradigm, precondition the trial design with repeated measures for averaging temporal waveforms within an exploratory framework. An expected total of at least 200 participants will be recruited over the course of the study. The aim is to recruit for a distribution of age, gender and participants that are involved in studies or practices of architecture, visual arts or related to maximize statistical significance regarding the targeted population segment.

Discussion: This study aims to investigate the cardinality of discriminative neural patterns correlated with the presentation of complex visual stimuli by detecting subcomponents of these neural phenomena using the designed system on short and prolonged periods of time and involving participants from architecture, visual arts or related fields. Subsequent results will bring to further discussion the role of visual experience in such system and the range it might address in the population segment.

Trial Status: The first phase of the study has been submitted for non-clinical trials and approved by ETH Zürich Ethics Commission on the 02nd July 2021 and given the registration ID: EK 2021-N-106. The first trial has been approved on August 1st 2021

Keywords: BCI; ERP; RSVP; EEG; CAAD; Visual Discrimination; Non-Clinical Applications

Introduction

Background

A brain-computer interface (BCI) is an interface that provides means of communication between the central nervous system (CNS) and computers or computerized devices (eg. robotic prosthetic limbs, motorized wheelchairs). It streams information from ongoing cognitive activity while bypassing peripheral nerves [49, 52, 51]. It originally allowed the development of rehabilitation applications for natural communication and environmental control by perfecting the classification accuracy of imaged mental tasks based on two opposite kinds of invasiveness into the body for data acquisition [52]. In that regard, the use of electroencephalography (EEG)-based BCI represents the most employed non-invasive technique due to its versatility, low cost/resolution ratio, and information transfer rate [27, 37]. The different levels of interaction in producing a neural response with a BCI are further divided into 3 main kinds of BCI models: active BCI (aBCI) that involves the conscious modulation of CNS activity from a user and independently of external stimulations, reactive BCI (rBCI) that involves external stimuli for a user to indirectly modulate the neural activity, and a passive BCI (pBCI) that involves spontaneous and involuntary neural activity from a user without being subject to active modulation or stimulation [53, 9, 42, 5, 35]. Interactions which are reactive and task-relevant are considered synchronous in time/frequency to an ongoing neural activity [38, 24, 44]. BCI systems of the asynchronous kind interact with self-paced neural responses and independently from elicitation [34, 39, 11]. Concurrently to the development of these techniques and subsequent methods researched independently or in a combined fashion to benefit from complementarity [6, 54], a wide range of potential future applications appeared on the horizon to broaden the field of research beyond control and communication, and beyond the medical field, including healthy subjects [26, 12, 4]. Regarding the involved ongoing cognitive activity, two main kinds of neural phenomena may be observed and processed within a BCI system. On one side, exogenous responses that are produced while attending to a particular external stimulus under selective attention and are generally characterized by either transient or steady-state evoked potentials. On the other side, endogenous responses which are self-paced and can either be conditioned under cognitive efforts and biofeedback or totally independent from any external stimulation [46].

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Rationale

A great part of BCI research has so far, been focusing on interactions using exogenous responses under selective attention with synchronous and reactive methods [38] for clear relation with controlled stimuli and the widespread applicability of the methods. Over the two past decades, event-related potentials (ERP) have become more and more investigated for a broader community of BCI researchers due to the relatively little amount of training necessary for a system to perform [16] and their detection across diverse modalities of acquisition [14] to correlate with the sensory discrimination of dedicated stimuli. ERP can be found in the amplitude variations of EEG signals associated with the onset of a stimulus presented to a subject [31]. The amplitude of ERP is quite smaller ($< 10\,\mu V$) than an ongoing EEG activity ($50\,\mu V$ to $100\,\mu V$). ERP elicitations are a time function of the frequency of appearance of a specific stimulus and can therefore be detected by averaging epochs over repeated trials in a temporal waveform [22] with a categorization of negative and positive voltage deflections known as ERP components [33]. In direct consequence to their time/frequency dependence of prior stimulation, their most frequent mode of elicitation is through the rapid serial presentation of an oddball paradigm [22], where a peculiar target to identify (the oddball) is placed among non-target stimuli. In recent years researchers have used ERP in studies involving rapid serial visual presentations (RSVP) to identify and distinguish static images, objects, scenes, and videos of increasing complexity [25]. In RSVP, a series of stimuli are presented to the subject at the same spatial location and at a relatively fast pace in order to differentiate between target and non-target stimuli [45]. The correlated and time-dependent neural responses are correspondingly detected by EEG and further analyzed using signal processing, feature extraction, and classification methods [29, 28]. The proposed BCI study aims to observe the EEG detection of ERP components and correlated neural phenomena under RSVP of complex stimuli and devise processing methods that would generalize their classification for applications in computer-aided architectural design (CAAD) where visual complexity becomes an intrinsic feature of the tasks.

Methods/Design

Objectives

The main objective of the study is to investigate and generalize the cardinality of classified neural patterns involved in the discrimination of complex visual scenery for the design of BCI models in future CAAD applications. Its objective is exploratory and twofold:

evaluating data processing and stimulus presentation methods, as well as the evolution of similar responses in repeated measures intra- and inter-subjects in non-clinical states.

Hypotheses

Logical discrimination is generally framed by 4 distinct classification outcomes labeling an instance whether or not to be positively mapped to a label [13]. While it is widely used in BCI classification methods, in correlation with labeled stimuli under attention (eg. BCI speller), it becomes insufficient or even inappropriate when lacking labels and elicitations come from complex and ambiguous inputs. Classes may become unbalanced, and labels absent from the design of the task [47, 18]. There should be, however, a minimal amount of found classes involved in particular sensory discrimination under a logical framework, once provided with a standardized presentation of these stimuli [8, 7]. Their cardinality should remain independent from the informational complexity of the stimulus but should be factored by cognitive parameters linked to attention such as stimulus probability [41], mental workload [1], and the user's literacy in practicing with BCI [50]. Moreover, the separation of these classes under uncertainty should allow for a generalization inter-session and inter-subject given the development of adequate adaptive learning methods on a prolonged usage basis [40].

Population Segment

Based on the availability of synthetic data covering the largest region including samples which will be taken along the research [1], a general distribution was observed from the reported evolution of the population in the Europe region and related to the field of architecture during the last 10 years between 2010 and 2020 **??**. It is to be noted that Switzerland is only reported for the year 2014. Since we envision to evaluate the capacity of our study to spread over the targeted population segment, and the size of the sample over the span of the research will not manage to significantly represent the reported population of 560 000 architects in Europe, the initial stratified sampling used for a general picture is limited to age and gender. It is reported that about 62% of that population is making daily use of 3D modeling among other CAAD practices involving complex visual digital environments (eg. BIM, Rendering, ...). We therefore assume that this ratio of digital/visual literacy should be reflected during pre-screening and that a finer granularity in terms of experience and training from education to practice should be reported in the sampling questionnaire. The age/gender sub-sample below 30 years of age will be extended further with students sample of equal gender ratio (58/42, male/female) from initial bachelor studies to doctorate. We also assume that the digital/visual literacy supposed to emulate performances during experiments [2] should not only apply to architects but also practitioners with intensive education on that matter (eg. visual arts). Therefore a subsample of students and practitioners of these sectors will be added with a similar age/gender stratification. Finally, another control group will be added with no education or practice on that matter from different sectors.

Figure 1 Evolution of the population working in architecture in the Europe region from 2010 and 2020. Architect's Council of Europe, ACE Sector Study 2020, https://www.ace-cae.eu/activities/publications/

Paticipants

All participants will be healthy and asked prior to the experiments if they are at least 18 or more years old. Participants would have been rejected if they ever had an epilepsy, seizure, physical or mental disorders, skin contact allergies, or are susceptible to motion sickness. Participants should not be taking any medication which might affect their cognitive capacities (eg. stimulants, depressants, or opioids), as well as alcohol and other recreational drugs during the study. Additionally, prisoners and pregnant women will not be considered due to vulnerability factors. The recruitment of the participants will be focused on those who are involved in studies or practices of architecture, visual arts or related. They must be exposed to 3D modeling and CAAD software with a varied range of experience and should be able to converse and read the English language for fluent understanding of the experiment and communication with the research team. Although it is not part of the study, the following general assumption regarding visual experience and discriminatory performances motivates the specific segment of population for this experiment. As participants with such background may be exposed more often to complex visual contexts, their visual cortex may outperform as compared to participants that are not related to above mentioned fields and due to accrue visual experience during dedicated education and practice. Another motivation for this segment concerns the larger scope of interest for the research project in which this study is taking part and aims at applications in the aforementioned fields. Hence the population segment should reflect the potential end-users.

[1]The Architect's Council of Europe Observatory: https://aceobservatory.com/Home.aspx?Y=2020&c=Europe&l=EN

Participants must not have any personal or professional relation to the research team. That is exclusive of personal relatives and students which might be or would become under performance evaluations by members of the research team, as well as peers or colleagues involved in collaborations with the research team or employed by them. Participants must be foreign to the research project team and the hosting research institute. Questionnaires will be given to the participants before and after they perform the experiment for personal information and to reflect the feedback of the participants by self-assessment regarding the experiments. The study will be conducted with full knowledge and consent of the participant regarding the acquisition and preservation procedures of the data, without any deliberate misinformation. Personal information reported in questionnaires will be kept confidential and to a necessary minimum. Self-assessment questions will be comprised of performances of attention and comfort during the experiment. Personal information questions will be comprised of contact, age, gender, exposure to digital tools in the participants daily work and work sector. After anonymization, this information will be fully detached from the participant's identification. Every participant will be received on an individual basis for the entirety of the experiment and each individual session will be run sequentially. No other participants or individual will be present in the room during the session, apart from the research team. Moreover, participants will be asked to sign a consent form approved by the Ethics commission of ETH Zurich. Participants will be compensated financially for each time they take part to an experiment, with 10.0-CHF in cash with receipt and regardless of their performances. In addition, participants will be offered non-alcoholic beverages post experiments for resting periods during the handling and filling of written forms.

Randomization

Upon completion of consent and baseline data collection, a computer-generated random number assignment will be set for each participant. The participant's number will become the unique identifier for data collection and analysis. The collected data will remain in a pseudonymized form for a period of 1 month after the experiment. An alphanumeric key will be given to each recorded datafile (eg. *YY-GP-00-00*: Year, Group, Participant number by order of acquisition, trial number). For both contact tracing and groups of participants whose participation would extend to future studies, a correspondence table between the pseudonyms and participants' real IDs is kept by the principal investigator on the data management repository. During that period of 1 month, it will be possible for the participants to access their own data upon request. Once that period has passed, the correspondence table will be deleted, except for groups with extended participation (willing to take part in future studies) and which table will be deleted after a similar period at the end of their participation. Since data will be made available publicly online to accompany published results, a complete anonymization will be performed prior to publication.

Study Settings

The study is divided into 4 phases of offline-online experiments across its timeline. Offline experiments are used to study and validate base methods across the BCI system, and online experiments are used to validate their modifications for application usage. Each of these experiments are framed by cross-sectional (CS) and longitudinal sub-studies (LS). Where CS sessions of several minutes are punctual and occur once for a participant, and LS sessions of several minutes occur repeatedly over several days given appropriate training schedules for the same participant [19, 40]. CS ensures the study and validation of both developed methods and paradigm, while LS allow for the study of mutual learning (ie. the participant, machine, and application) in adaptive methods to increase and stabilize the separation of found discriminating patterns. Offline experiments are typically designed as "open-loop" with no feedback provided to the participant during stimulus presentation, while online experiments are designed in both "open" and "closed-loop" with a feedback in order to compare performances. Data collected during LS offline experiments will also be used to augment the training data for CS online studies when appropriate (eg. involved in adaptive methods). For each new phase, a new experimental paradigm is designed for the diversity of the project (will be reflected in subsequent applications for ethics approval). The diversity of the experimental paradigms in each phase will allow to have multiple data sets which will play a crucial role in offline training and afterwards, when monitoring online testing. The participants will be involved in experiments consisting of a RSVP with an oddball task for the detection of visual ERPs using an EEG-based BCI system in a synchronous loop.

Trial Design

The chosen neural phenomena and study (ie. ERP), as well as the presentation paradigm (ie. RSVP oddball), precondition the trial design with repeated measures for averaging temporal waveforms within an exploratory framework. Since the targeted classification problem concerns more than two classes, stimuli will

be arranged in random distributions of target, non-target and distractors visual stimuli during offline experiment. Their distribution will be maintained close to a range of 20% (targets) - 60% (distractors) - 20% (non-targets) in each randomized sequences repeated enough times to ensure the prior probability of presenting a stimulus for than once in a run repeated itself several times in a session to the extent of a maintained attention [25]. Each run is followed by resting periods of a few seconds. Flashed and non-flashed stimulations are kept within range of the time window of a second which will tentatively decrease over the course of the study for performance evaluations while managing overlaps of eventual ERP. During, early phases of the study, sessions will be subdivided with supervised and unsupervised stimulation for studying the transfer of found discriminative classes upon unlabeled stimuli of increased complexity.

Outcomes and Measurements

Primary outcomes consist in expected increasing performances of classification accuracy, as well as the maintained separability of found classes. To that end, two approaches will be combined: averaged measured responses from participants in order to assess the evolution of a capacity to produce more stable and distinct patterns, the performance measurement of predictors. The Area Under the Curve (AUC)of Receiver Operating Characteristic (ROC) will represent the main measurement of multi-class classification accuracy [23, 3]. Significance of classification metrics under a practical level of chance [36] will be also designed for pondering the accuracy with the designed BCI system. Progresses on the user's end will be measured first with Run-Wise Cross Classification Accuracy (RWCCA) for assessing improved separability [30]. Performances of the overall designed BCI system will be assessed in terms of rate of information transfer with practical measurements such as the Rate of Information Gain (RITG) [17] and Practical Bit Rate (PBR) [48] over the typically used Information Transfer Rate (ITR) [43]. Secondary outcomes aim at providing an increased variance resulting from the use of designed BCI-CAAD compared to traditional methods. Towards the end of the study, a later experiment will be designed with a control group assigned to discriminate the same stimuli without BCI-RSVP system to assess differences in resulting variances. Initial collection of EEG data will be performed with a semi-dry (water-based) 32 channels acquisition device providing contact and active shielding. Electrode are placed according to the 10-20 system [21] at the following locations: FP1, FPz, FP2, AF3, AF4, F3, Fz, F4, FC1, FCz, FC2, C3, Cz, C4, CP5, CP1, CPz, CP2, CP6, P7, P3, Pz, P4, P8, PO7, PO3, POz, PO4, PO8, O1, Oz, O2, with ground on AFz and the reference on the right mastoid. Data is digitized at a sampling rate of 24 bits and 256Hz.

Sample Size

An expected total of at least 200 participants will be recruited (50 participants for each phase) over the course of the study. The aim is to recruit for a distribution of age, gender and participants that are involved in studies or practices of architecture, visual arts or related to maximize statistical significance regarding the population segment. As per authors best knowledge there are no identical pilot study nor previous studies [25]. This pilot study will serve the assessment of an adequate sample size for LS and CS study of the next phases.

Statistical Methods

In order to analyze and compare means of classification performances between classes using machine learning algorithms population-wise, multivariate analysis of variance (MANOVA) will be used in the study. Moreover, to overcome the findings that are false and unreplicable but statistically significant for an ERP study. Luck and Gaspelin have discussed multiple approaches to avoid the bogus yet statistically significant results among group or conditions. In this study collapsed localizers approach will be used in which the data will be averaged across the conditions, and then the time range and electrode sites showing the largest activity will be used when measuring the activity in those conditions [32].

Risks

This study is assessed to be of risk category A according to the Swiss Ordinance on Human Research with exception of clinical trials [2]. Given the participants' selection criteria, the non-invasive types of data acquisition, the non-clinical purpose of the research and the anonymization of recorded data, risks are reduced to their expected minimum. Data collection will be performed solely from the exposed surface of the scalp, in a non-invasive and non-energy-transmitting fashion via EEG. Possible damages to health, which are directly related to the study and are demonstrably the fault of ETH Zurich, are covered by the general liability insurance of ETH Zurich (Insurance Policy No. 30/4.078.362 of the Basler Versicherung AG). Beyond the before mentioned, the health insurance and the accident insurance (e.g., the commute to or from the study location) is participants entire responsibility.

[2] https://www.fedlex.admin.ch/eli/cc/2013/642/en

Discussion

This study aims to investigate the cardinality of discriminative neural patterns correlated with the presentation of complex visual stimuli by detecting ERP's components using RSVP-based EEG-BCI system on short and prolonged periods of time and involving participants from architecture, visual arts or related fields. In recent decades numerous studies have been conducted using RSVP-ERP based BCI's in order to determine the performance of the subjects during the presentation of different visual stimuli [25, 20, 10]. However, the challenges to apply such discriminative capacity of complex visual stimuli in multi-class scenarios for application aims is yet to be answered and adequate methods to be designed. This study aims to become a benchmark to investigate the generalisability and limitations of the designed system for CAAD applications. Subsequent results will bring to further discussion the role of visual experience in such system and the range it might address in the population segment. Eventually, the overall benefits of applying BCI methods to CAAD should be reflected in an increased resulting variance of produced design solutions. Expected secondary outcomes will be used in the goal to ponder primary ones within the scope of generalization.

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Abbreviations
AUC: Area Under the Curve
BCI: Brain-Computer Interface
aBCI: Active BCI
pBCI: Passive BCI
rBCI: Reactive BCI
BIM: Building Information Modeling
CAAD: Computer-Aided Architectural Design
CNS: Central Nervous System
CS: Cross Sectional Study
EEG: Electro-Encephalography
ERP: Event-Related Potential
LS: Longitudinal Study
MANOVA: Multivariate Analysis of Variance
ROC: Receiver Operating Characteristic
RSVP: Rapid Serial Visual Presentation
RWCCA: Run-Wise Cross Classifcation Accuracy

Availability of data and materials
The dataset(s) supporting the conclusions of this study will be made available in the ETH Research Data Collection repository https://www.research-collection.ethz.ch/), unique DOI links will be attributed and listed in both subsequent publications and the project's website (https://neuramod.arch.ethz.ch/outcomes/). Each datasets will be formatted according to the BIDS standards [**pernet˙eeg˙2019**, 15].

Ethics approval
The first phase of the study has been submitted for non-clinical trials and approved by ETH Zürich Ethics Commission on the 02nd July 2021 and given the registration ID: EK 2021-N-106. The first trial has been approved on August 1st 2021. Subsequent submissions will be done similarly on a trial basis at the beginning of each phase. Recruitment of participants for the study began immediately after approval. Initial data collection and intervention are scheduled to take place between at the end of the year 2021. Subsequent studies will follow similar procedures 6 months prior to their starting dates.

Competing interests
The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Authors' contributions
P.C. conceptualized the study. Both P.C. and N.K.Q. contributed equally to the rest of this article.

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Figures

Figure 1

Evolution of the population working in architecture in the Europe region from 2010 and 2020. Architect's Council of Europe, ACE Sector Study 2020,

https://www.ace-cae.eu/activities/publications/